Turkish Journal of Science & Technology
15(2), 101-110, 2020

ANN-Based MPPT Algorithm for Photovoltaic Systems

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(Geliş/Received: 07/07/2020; Kabul/Accepted: 23/08/2020)

Abstract: It is very important to get maximum efficiency from photovoltaic panels with low yields. To be able to achieve high efficiency from panels, maximum power point tracking algorithms have been developed. Perturb&Observe and incremental conductance methods, which are among the conventional methods, are not very successful in capturing the points from which maximum power can be obtained in variable atmospheric conditions. In this article, a maximum power point tracking method based on the artificial neural network was proposed. In the proposed method, artificial neural network inputs were designed as temperature and voltage, while its output was designed as the reference voltage. By controlling this reference voltage through a PI controller, it was ensured that the system generated maximum power in variable atmospheric conditions. Conventional methods and the proposed method were compared by simulation studies conducted in the MATLAB/Simulink environment. The superiority of the proposed method was demonstrated with a compelling scenario in which temperature and radiation were constantly changing.

Key words: Photovoltaic System, Artificial Neural Networks-ANN, Boost Converter, MPPT Algorithms.

Fotovoltaik Sistemler için YSA Tabanlı MPPT Algoritması

Öz: Verimleri düşük olan fotovoltaik panellerden maksimum oranında verim elde etmek oldukça önemlidir. Panellerden yüksek verim elde etmek için maksimum güç noktası izleme algoritmaları geliştirilmiştir. Geleneksel yöntemlerden olan Değiştir&Gözle ve Artımsal İletkenlik yöntemleri, değişken atmosferik koşullarda maksimum gücün elde edileceği noktaları yakalamada çok başarılı değillerdir. Bu makalede yapay sinir ağı tabanlı bir maksimum güç noktası izleme yöntemi önerilmiştir. Önerilen yöntemde yapay sinir ağının girişleri sıcaklık ve gerilim, çıkışı ise referans gerilim olacak şekilde tasarlanmıştır. Bu referans gerilim bir PI kontrolör tarafından kontrol edilerek sistemin değişken atmosferik koşullarda maksimum güç üretmesi sağlanmıştır. Geleneksel yöntemler ile önerilen yöntem MATLAB/Simulink ortamında yapılan benzetim çalışmaları karşılaştırılmıştır. Önerilen yöntemin üstünlüğü, sıcaklık ve radyasyonun sürekli değiştiği zorlayıcı bir senaryo üzerinde gösterilmiştir.

Anahtar kelimeler: Fotovoltaik Sistem, Yapay Sinir Ağları-YSA, Yükseltici Tip Dönüştürücü, MPPT Algoritmaları.

1. Introduction

Reduced energy sources, increased environmental pollution, and global warming have increased the interest in renewable energy sources. Among the renewable energy sources, the most intensively used energy source is the sun. Since efficiencies of solar panels are low, maximum efficiency from the panels is obtained by using the maximum power point tracking (MPPT) algorithms. The ability of these MPPT algorithms to operate under variable atmospheric conditions is very important because it will increase efficiency [1].

Many studies related to MPPT algorithms have been carried out so far and it still continues to be developed today. Incremental Conductance (IC), Perturb & Observe (PO), Constant Voltage Controller (CVC), Artificial Intelligent (AI), and Hybrid methods, which were among the conventional methods, were compared [2-3]. In addition to the fact that the PO method causes oscillations that are inevitable in the steady-state, its performance is also low in variable atmospheric conditions. Therefore, modified PO methods have been developed. These algorithms have been tested and compared under variable atmospheric conditions [4-6]. In addition to modified PO methods, in another research, the superiority of a new PO algorithm, effective in partial shading conditions, was demonstrated by an experimental study [7].

The success of a variable step IC method, which was proposed as an alternative to the IC method and comprised of a table, was demonstrated experimentally [8]. High-performance MPPT algorithm studies with the Fuzzy Logic Controller (FLC) method is quite common. An MPPT algorithm, which consisted of IC and Fuzzy Logic estimator and operated with high performance in radiation changes, was experimentally realized [9]. The performances of two different hybrid MPPT algorithms consisted of PO-FLC and IC-FLC were examined in fast-

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changing weather conditions. It was seen that the performance of the IC-FLC hybrid algorithm was slightly superior to the performance of the PO-FLC algorithm [10]. In a different study, on the other hand, by using the System Identification (SI), a high-performance MPPT algorithm that can operate under variable atmospheric conditions was developed [11]. In this method, power generation with high performance was achieved both in temperature and radiation changes compared to the conventional methods.

The Artificial Neural Network (ANN) structure is used in motor control applications, measurement of EEG signals, and MPPT algorithms [12-14]. With the becoming prevalent of MPPT algorithms, comparison studies have been conducted to show the advantages of various algorithms [15]. In one of these studies, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), PID, FL, and ANN methods were compared. Temperature and radiation values were used as input values in the ANN method [16]. In another study, a variable step ANN algorithm was developed and experimentally demonstrated to reduce high tracking performance, overshoot amount, and steady-state ripples [17]. A hybrid MPPT algorithm, which operates with high-performance both under rapidly changing atmospheric conditions and in partial shading conditions, was developed by combining the ANN and PO methods. Temperature and radiation data were used in the inputs of the ANN algorithm [18]. In another study where temperature and radiation values were used as inputs of the ANN algorithm, a comparison of conventional methods and the ANN method was made [19]. A three-layer and three-input ANN algorithm that determined the global MPP point under partial shading conditions was developed. The proposed algorithm was realized by using FPGA [20]. In another study, the ANN structure, where temperature and radiation values were used as input, was realized in the Simulink environment. It was shown that the experimental results obtained by using the proposed structure in a real system were the same as the simulation results [21].

In this study, an ANN structure with two inputs, three layers, and ten neurons was proposed to perform the MPPT algorithm in Photovoltaic (PV) power systems. In conventional ANN structures, either current and voltage information or radiation and temperature information are used as input. In the proposed ANN structure, on the other hand, voltage information and temperature information were used as input. The output information of this ANN structure constitutes the reference voltage. When the proposed method is operating under variable atmospheric conditions, it generates a reference voltage depending on the change of temperature and radiation. The reference voltage is controlled with a PI controller by comparing it with the voltage of the PV panel. The PO and IC methods, which are among the conventional methods, and the proposed method were compared by the simulation studies conducted in MATLAB/Simulink environment.

2. PV Cell Model

The model of a PV cell is seen in Figure 1. This PV cell model consists of a current source, a diode connected inversely and parallel to this current source, a parallel-connected resistor, and a series-connected resistor [22]. Mathematical equations of the PV cell model are shown in the equations between Equation 1 and Equation 3.

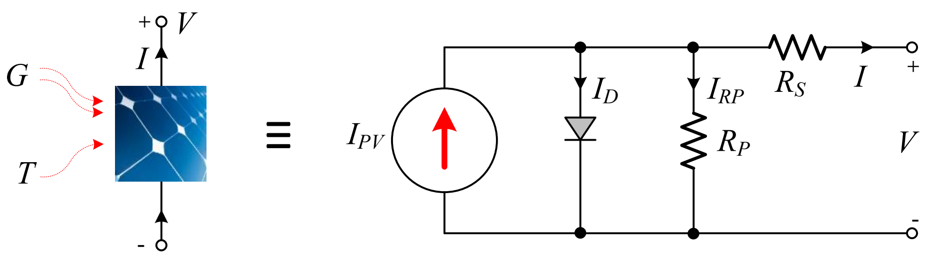

Figure 1. Electrical equivalent circuit model of PV cell

$$I = I_{PV} - I_D - I_{R_P} \tag{1}$$

$$I = I_{PV} - I_0\left[exp\left(\frac{V+R_S I}{a}\right) - 1\right] - \frac{V+R_S I}{R_P} \tag{2}$$

$$a = \frac{N_s n k T}{q} \tag{3}$$

where I_0 is called the reverse saturation current or leakage current of the diode. a is the ideality factor, N_s is the number of serial-connected cells, n is the diode ideality constant, k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), T is the cell temperature (Kelvin), and q is the electron charge ($1.60217646 \times 10^{-19}$ C). The current generated by the PV cell by the effect of light is given in Equation 4.

$$I_{PV} = \left(I_{PV,n} + K_I(T - T_n)\right)\frac{G}{G_n} \tag{4}$$

where $I_{PV,n}$ refers to the current generated for 25 °C and 1000 W/m^2, T_n refers to the nominal temperature (Kelvin), G refers to the radiation value on the panel surface (W/m^2), and G_n refers to the nominal radiation value (W/m^2). The saturation current of the diode (I_0) is given in Equation 5.

$$I_0 = \frac{I_{SC,n} + K_I(T - T_n)}{\exp\left(\frac{V_{OC,n} + K_V(T - T_n)}{a}\right) - 1} \tag{5}$$

where $I_{SC,n}$ is the nominal short-circuit current, $V_{OC,n}$ is the nominal open-circuit voltage, K_I is current coefficient, and K_V is voltage coefficient.

Based on the cell model, the current-voltage and power-voltage graphs of a PV panel are shown in Figure 2. The current-voltage and power-voltage graphs of a 10 kW PV power system created in the MATLAB/Simulink environment in this study by depending on the cell model described above are shown in Figure 2. I-V and P-V curves of the power system are given in Figure 2(A) under a constant temperature of 25°C and for different radiation values and in Figure 2(b) under constant radiation of 1000 W/m^2 and for different temperature values.

Array type: Trina Solar TSM-250PA05.08; 10 series modules; 4 parallel strings

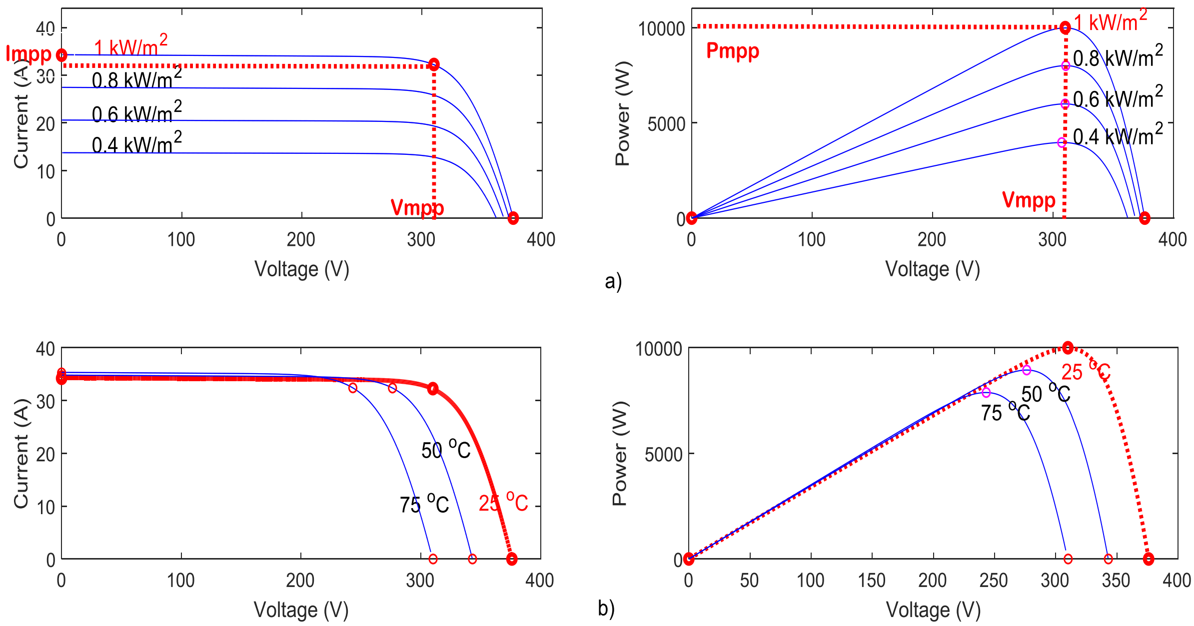

Figure 2. I-V and P-V curves of the PV system; a) at a constant 25°C and at different radiation, b) at constant 1000 W/m^2 and at different temperature values.

As can be seen in the graph, the power generation of the panel can vary depending on atmospheric conditions such as radiation and temperature. This variability affects the efficiency of the system. In terms of the efficiency of the power system, operating at a constant power point improves the efficiency of the system. In this respect, the maximum power point required for constant power applications is determined by the help of Buck-Boost converters and MPPT algorithms.

3. DC-DC Converter and System Model

The system model, consisting of a PV panel, ANN-based MPPT algorithm, and boost-type DC-DC converter is shown in Figure 3. The boost-type converter increases the V_S voltage applied to its input by depending on a specific conversion rate. The relation between the output voltage (V_0) and the input voltage (V_S) of the converter is given in Equation 6.

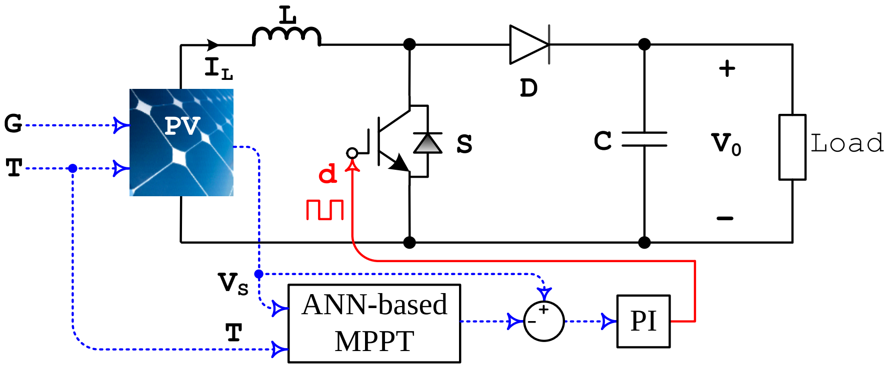

Figure 3. DC-DC Converter and System Model.

$$V_0 = \frac{V_S}{1-d} \tag{6}$$

where d refers to the duty cycle of the S switch, V_S refers to the panel output voltage, and V_0 refers to the converter output voltage. While the panel output voltage (V_S) is decreasing depending on atmospheric conditions, the duty cycle (d) is increased by the ANN-based MPPT algorithm in order to keep V_0 constant.

4. Conventional MPTT Methods
4.1. PO Method

In the conventional PO method, the magnitude of the step voltage change (ΔV_{ss}) at each step is constant. Therefore, for different values of ΔV_{ss}, the error amount and speed of the system response will be different. Small step changes reduce oscillations around the maximum power point, while they increase the time to reach maximum power. In large step changes, on the other hand, the maximum power point is reached much faster, but the oscillations that occur in the power around the maximum power point increase. In fast-changing weather conditions, this method either fails to track the MPP point or tracks it in such a way that it causes massive time and power losses. As seen in Figure 4(a), while the voltage increases in the blue zone to the left of the P_{MPP} point, the power also increases. In the Orange area to the right, on the other hand, while the voltage is increasing, the power is decreasing. P_A<P_B at the right of Point B, while PA>PB at the region to the left of it. Depending on the magnitude of the step-change, this condition can lead to an error in the calculation of power, and therefore, it is considered a disadvantage of the PO method.

4.2. IC Method

The conventional IC algorithm operates according to the principle of I/V exchange. In this method, the measured instantaneous voltage and current values are compared with the previous voltage and current values. The maximum power point is attempted to be captured by comparing the obtained increasing conductivity value ($\Delta I/\Delta V$) with the instantaneous conductivity (I/V). The output power at the P_{MPP} point where the maximum power is obtained from the PV system is expressed with Equation 7.

$$P_{MPP} = V_{MPP} x I_{MPP} \tag{7}$$

Equation 7 is shown in the differential equation as follows.

$$\frac{dP}{dV} = \frac{d(IV)}{dV} = I + V\frac{dI}{dV} \tag{8}$$

$$\frac{dI}{dV} \cong \frac{\Delta I}{\Delta V} \tag{9}$$

$$\frac{dP}{dV} = \frac{d(IV)}{dV} = I + V\frac{\Delta I}{\Delta V} \tag{10}$$

If Equation 10 is solved for 3 different regions shown in Figure 4(b); it is obtained;

in the blue zone to the left of the P_{MPP} point $\quad \frac{dP}{dV} > 0,\ \frac{\Delta I}{\Delta V} > -\frac{I}{V}$ (11)

at the P_{MPP} point $\quad \frac{dP}{dV} = 0,\ \frac{\Delta I}{\Delta V} = -\frac{I}{V}$ (12)

in the orange zone to the right of the P_{MPP} point $\quad \frac{dP}{dV} < 0,\ \frac{\Delta I}{\Delta V} < -\frac{I}{V}$ (13)

This method requires a high sampling rate in the tracking of the power change.

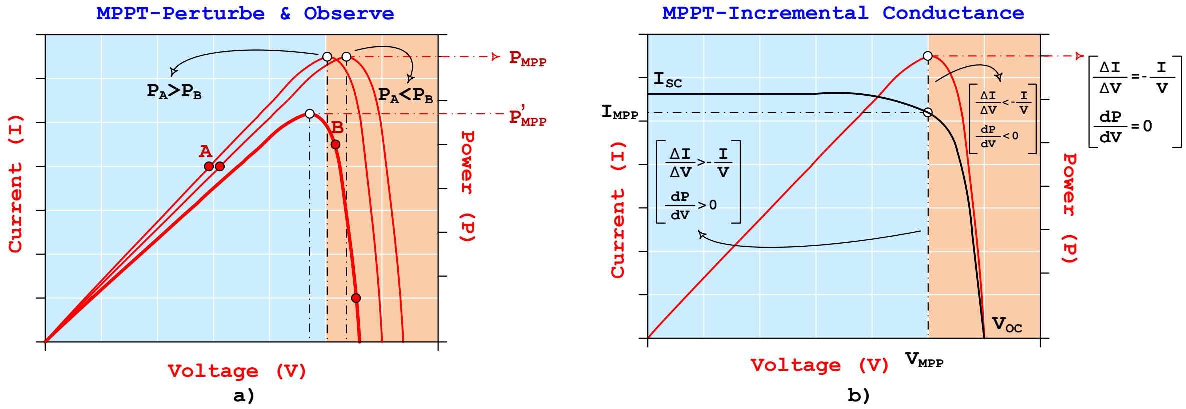

Figure 4. Conventional MPPT methods. a) Perturbe&Observe, b) Incremental Conductance

4.3. The Proposed ANN Model

In recent years, ANN has been being used for estimation and control purposes both in many different systems and in MPPT algorithms. There are quite a lot of studies related to this subject in the literature. ANN is a computation tool often used in nonlinear systems. It is defined by the properties of biological neurons, which consist of weighted connections used to send signals to each other. The weights used in the input values are set by the learning rule in the training process. In this study, an ANN structure with two inputs, ten neurons, and one output was proposed and it is shown in Figure 5.

As shown in Equation 14, the mapminmax function used in the ANN structure is used to normalize input values. In the hidden layer, the tansig function given in Equation 15 was used as the activation function. Normalized values are converted to their normal values using the mapminmax_reverse function in Equation 16.

$$mapminmax = \frac{(x - x_{min})(x_{max} - x_{min})}{(y_{max} - y_{min})} + y_{min} \tag{14}$$

$$tansig = \frac{2}{e^{-2x} + 1} - 1 \tag{15}$$

$$mapminmax\_rever. = \frac{(x - y_{min})(x_{max} - x_{min})}{(y_{max} - y_{min})} + x_{min} \tag{16}$$

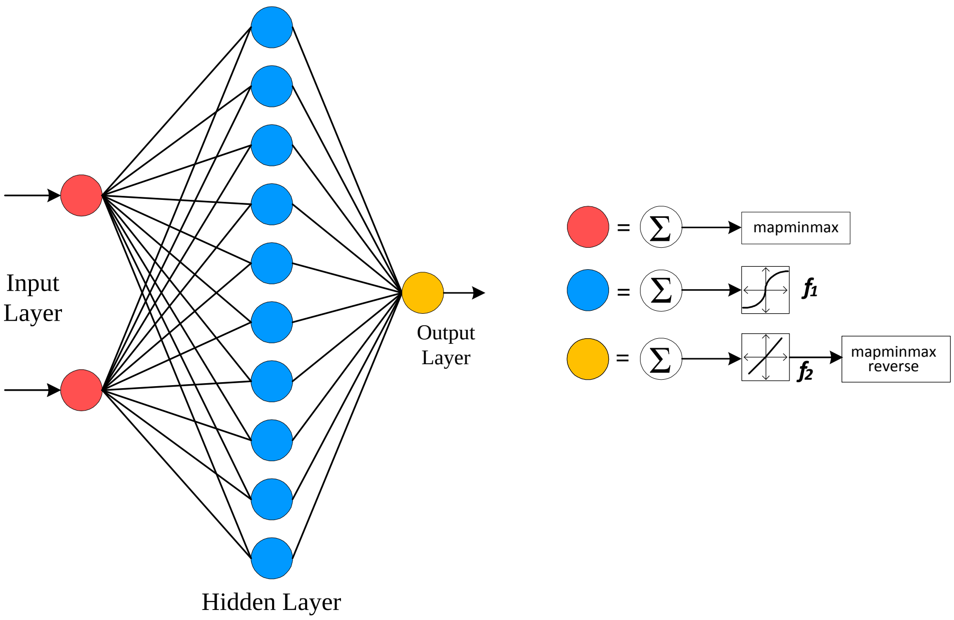

Figure 5. The proposed ANN structure.

As seen in Equation 14, the output neuron is obtained by summing each of the input signals after they were multiplied by the connection weights.

$$y_j = f\left(\sum w_{ij}x_i + b\right) \tag{17}$$

where f is the activation function, w_{ij} is the connection weight, x_i is the input signal, b is the deviation value, and y_j is the output neuron. The sum of the difference between the desired output value and the obtained value is seen in Equation 18.

$$E = \frac{1}{2}\sum_j \left(y_{dj} - y_j\right)^2 \tag{18}$$

where y_{dj} refers to the desired output value. In this study, the data required for the training of ANN were obtained in the MATLAB/Simulink environment. The number of data obtained for each input was 350000. 175000 of these data were used for training purposes, 70000 for verification purposes, and 105000 for testing purposes. As training algorithms, three different methods, Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG) and Bayesian Regularization (BR), were used. The success of the ANN was measured using mean square error (MSE) and regression coefficient (R^2). These performance criteria were given in Equations 19 and 20, respectively.

$$MSE = \frac{\sum_{i=1}^{n}\left(y_{p,i} - y_i\right)^2}{n} \tag{19}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_{p,i} - y_i\right)^2}{\sum_{i=1}^{n}\left(y_{m,1}\right)^2} \tag{20}$$

where n is the sampling size, y_p is the estimated value, y_m is the measured value, and y_i is the value of the sampled data. The best results were obtained using the Levenberg-Marquardt algorithm. It was determined that MSE =3.46425e-7 and R^2 = 0.99962. Simulation studies conducted using the proposed ANN structure are given in Section 5.

5. The Proposed ANN-Based MPPT Algorithm and Its MATLAB/Simulink Simulation

When studies in the literature were examined, it is seen that either current and voltage values or temperature and radiation values has been used as input in ANN-based MPPT algorithms. In some studies, on the other hand, power values have also been added to the ANN input. In this study, the ANN structure was created with different input values. As ANN inputs, temperature and voltage information were used. The output of the ANN is the reference voltage to be controlled. PV panel voltage is controlled through the PI controller by using this reference voltage. Thus, the ripple in the power of the PV panel occurs barely.

The proposed method revealed an impressive performance under variable atmospheric conditions in which both temperature and radiation values were changing rapidly and slowly. Because the voltage reference generated by the ANN structure provides adaptation to variable atmospheric conditions, this proposed method is also an adaptive method. The current of the panel was not measured in this study. In this way, an advantage was ensured in terms of the number of sensors compared to many studies. The MATLAB/Simulink block diagram in which the proposed method is used is given in Figure 6. The sampling time was selected as 5µs. The switching frequency of the boost-type DC-DC converter was taken as 20 kHz. ANN algorithms require large computation times for microprocessors. Therefore, the sampling frequency of the MPPT algorithm was determined as 1 ms in this study.

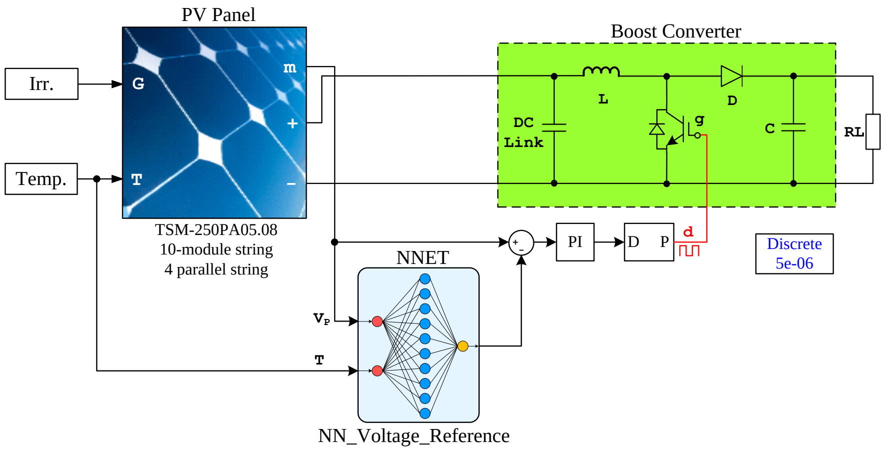

Figure 6. MATLAB/Simulink block diagram of the proposed ANN-based MPPT.

By creating a scenario in which radiation and temperature varied with different steps in different regions, IC, PO, and the proposed ANN-based method were compared. All three methods were tested under the same conditions in the comparison process. The temperature and radiation change scenario created for testing PO, IC, and the proposed method is seen in Figure 7.

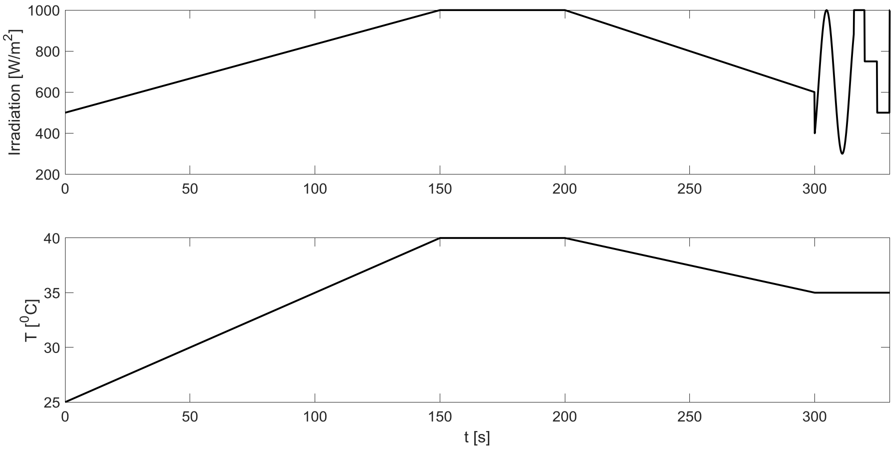

Figure 7. Radiation and temperature change scenario.

Figure 8 shows PV panel currents obtained by all three methods. Here, it is seen that there is no any ripple in the current waveform obtained by the proposed method.

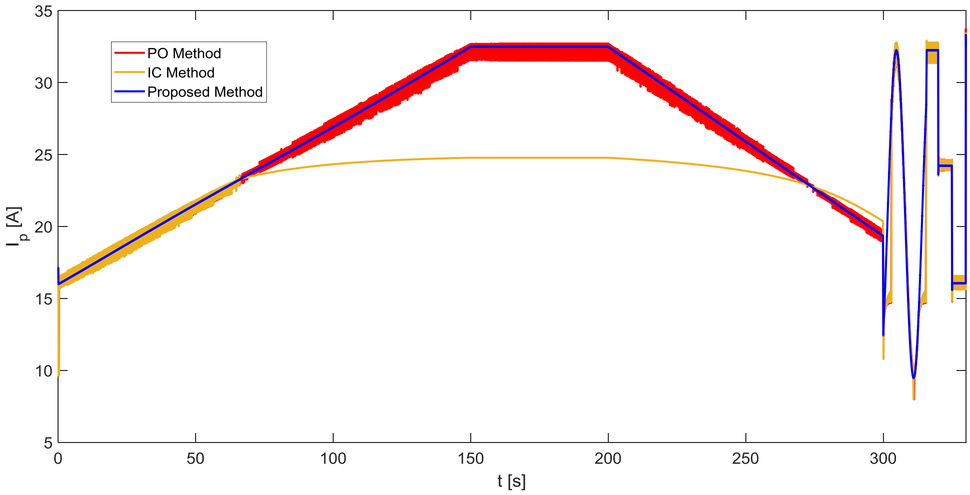

Figure 8. PV panel currents obtained for PO, IC and proposed ANN-based methods.

Figure 9 shows the obtained PV panel powers related to PO, IC and the proposed ANN-based method. Here, examinations were done in three different regions. In the first region, the steady-state was reached as earliest by the proposed method. In the second region, the IC method failed to track the maximum power point. In the PO method, the power ripple was quite high. In the ANN-based MPPT method, on the other hand, there was no power ripple. In the third region, whereas IC and PO were unable to track the maximum power point, the proposed method was successful. In the fourth region, the power ripple in the proposed ANN-based method was almost nonexistent compared to other PO and IC methods. In Figure 10, PV panel voltages obtained using each of the three methods are seen. Here, it is observed that the voltage obtained by the proposed method varies according to atmospheric conditions.

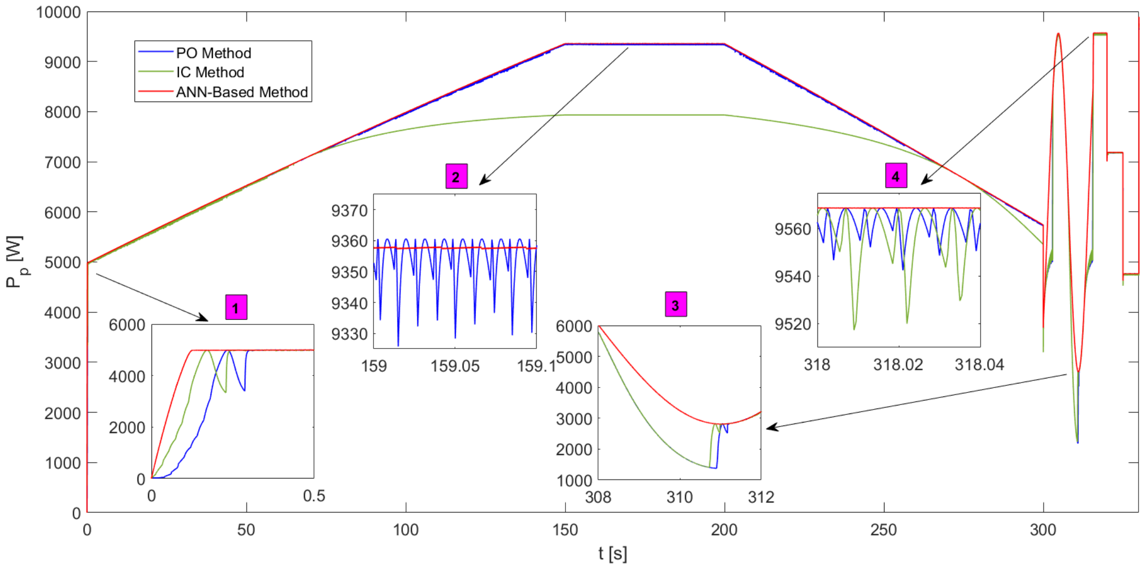

Figure 9. The obtained PV panel powers related to the PO, IC, and the proposed ANN-based methods.

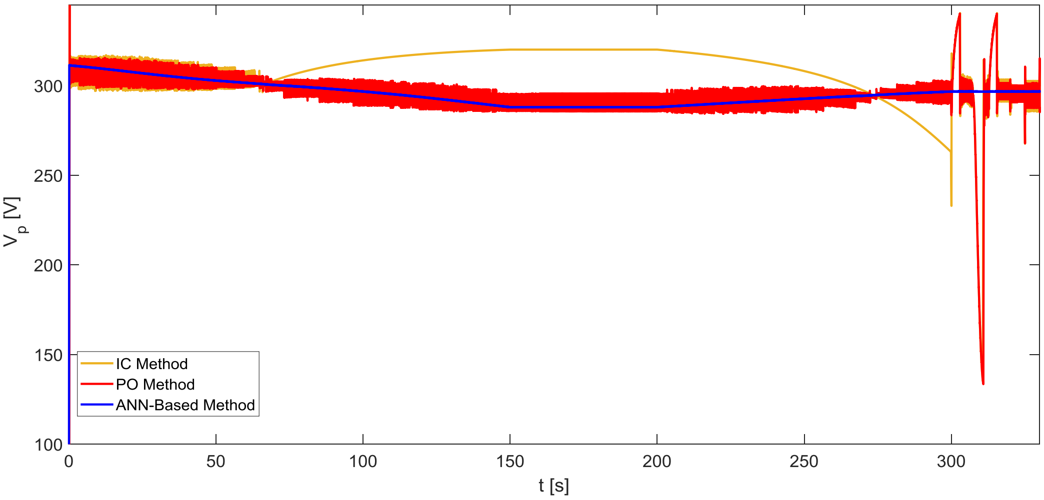

Figure 10. Obtained PV panel voltages related to the PO, IC, and proposed ANN-based methods.

6. Conclusion

It is quite important that MPPT algorithms operating under variable atmospheric conditions track the maximum power point. In addition to this, ripples that may occur in the PV power system are demanded to be low. Thus, the efficiency of the system is increased. There are many MPPT algorithms developed for this purpose. Conventional ANN methods are carried out by measuring either current and voltage or radiation and temperature values. In this study, an ANN-based MPPT method in which temperature and voltage data were used as input was proposed. In this proposed method, the output of the ANN structure constitutes the reference voltage, and this voltage is controlled by a PI controller. The performance of this ANN-based MPPT algorithm where temperature and voltage were used as inputs and which could operate under variable atmospheric conditions was discussed by comparing it to conventional PO and IC methods. In simulation studies, MPPT methods were tested using a scenario in which radiation and temperature values vary to create compelling conditions. In the proposed ANN-based method, the efficiency is highest as the amount of power ripple is minimum. It was seen that the proposed method was superior to the conventional methods in terms of both the fact that it could track the maximum power point in many different regions and the fact that the ripples in power were low.

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